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# ENHANCING THE QUALITY OF ROUTING (QOR) IN DATACENTRIC SENSOR NETWORKS

**Louisiana State University**

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This final report describes a new analytical framework within which reliable length and energy-constrained routing in sensor networks from reporting sensors to querying nodes can be examined in a quantitative manner using game-theory. In particular, different standard routing protocols can be compared and quantitatively evaluated with respect to reliability in conjunction to communication energy efficiency. It proposed sensor centric quality of routing metrics (labeled path weakness) and derived fundamental approximation limits on finding reliable energy-constrained routing paths with bounded weakness. Three new protocols were designed for length-energy-constrained routing in sensor networks. The performance of the protocols were evaluated with respect to standard geographic routing schemes for sensor networks. The results show that the proposed protocols balance energy equitable across network nodes and lead to sensor networks with longer lifetimes as compared to existing protocols.

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# Enhancing the Quality of Routing (QoR) in Datacentric Sensor Networks

GRANT # F30602-02-1-0198

## Final Status Report

### 1. Introduction

This final status report describes the outcome of the project titled `` Enhancing the Quality of Routing (QoR) in Datacentric Sensor Networks'' in support of AFRL and DARPA carried out by the participants from Louisiana State University during the reporting period. The purpose of the project was to develop new models for *reliable length and energy-constrained routing in sensor networks* that takes the `quality' of routing paths (measured in terms of its energy-effects on individual sensors) into account. The project utilized the following participants from Louisiana State University: Dr. Rajgopal Kannan and Dr. S. Sitharama Iyengar along with one graduate student, Miss. Lydia Ray, employed as a research assistant. The organization of this report follows the guidelines as set forth in the CDRL.

### 2. Project Information

### 2.1 Programmatic Information

Administrative data relevant to this effort is summarized below.

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## 2.2 Project Description

The following subsections provide a detailed description of the completed project. We first delineate the problem statements in the research objectives subsection followed by a detailed description of our technical approach to solving these problems.

### 2.2.1 Research Objectives

In what follows, we outline the major objectives of our research efforts by describing the problem statement, our research goals and the expected impact of our research efforts.

#### 2.2.1.1 Problem Description

Sensor networks are massively distributed systems for sensing and *in situ* processing of spatially and temporally dense data. They consist of large numbers of autonomous, interconnected sensory nodes (sensors) which continuously sense and store attributes of locally occurring phenomena and can be deployed on a large scale in resource-limited and harsh environments, such as seismic zones, ecological contamination sites or battlefields. Typically, network tasks are executed jointly by routing and cooperative processing of sensed information.

The untethered and unattended nature of sensors in wireless sensor networks severely constrains the types of feasible routing algorithms. In datacentric information routing, interest queries are disseminated through the sensor network for retrieving named data i.e., data satisfying specific attributes. Further, data can be aggregated or combined at intersecting nodes along the routing tree to reduce data implosion. Packets must be forwarded along low-cost paths; minimizing overall energy consumption (aggregate path energy cost) is one possible routing metric. However such routing strategies may result in uneven energy depletion across sensor nodes and expedite network partition. Thus it would seem preferable for sensors to forward packets based on local communication costs.

While *energy-efficiency* is an important parameter, several applications require the deployment of sensors in hazardous/hostile environments where sensors can fail or be compromised by adversaries and therefore the *reliability* of a data transfer path from reporting to querying sensor(s) is a second critical metric. However, reliable routing paths obtained through forwarding decisions based on local energy choices may be quite long, leading to energy depletion at more sensors while also increasing delay. Thus *path length* is a third critical routing metric affecting both energy efficiency and sensor lifetime.

Note that while energy costs are local, path reliability and path length are global or network-wide metrics. Thus, routing strategies for the sensor network must be derived by optimizing these criteria simultaneously. In other words, sensors must cooperate to maximize network wide objectives (such as reporting queries via reliable and short paths) without compromising their own survivability (as measured by their energy consumption). This paradigm can be labeled as sensor-centric. Sensor-centric network components have to behave intelligently to find the right trade-offs between efficient energy consumption and network-wide objectives. Obviously, network operability will be prolonged if a critically energy deficient node can survive longer by abstaining from a route rather than taking part for a small gain in overall reliability, latency or length.

#### 2.2.1.2 Research Goals

In this project, we consider the following performance issue that can be used to derive fundamental performance limits on routing in sensor networks: How do we evaluate the suboptimality of datacentric routing paths/trees in sensor networks? Such a `Quality of Routing' (QoR) metric is straightforward for traditional routing algorithms that optimize a single (end-to-end) attribute such as energy cost, reliability or latency. However, in the game-theoretic context where reliable energy-constrained routes in the network are derived as the equilibrium of sensor strategies, a new sensor-centric metric is necessary for evaluating and comparing different suboptimal paths. For example, one path may yield high payoffs for sensor $i$ with low payoffs for sensor $j$, while the exact opposite situation may prevail on another path. **Our goal is to define several sensor-centric QoR metrics for evaluating arbitrary routing paths based on the idea of node `weakness' and use these metrics to develop new routing protocols for energy-balanced and reliable routing in sensor networks**. This route evaluation paradigm essentially quantifies the suboptimality of a node participating in a given route, i.e., how much a node would have gained by deviating from the current path to an optimal one.

#### 2.2.1.3 Expected Impact

We have developed a new analytical framework within which reliable routing in sensor networks from reporting sensors to querying nodes can be examined in a quantitative manner. In particular, different standard routing protocols can be compared and quantitatively evaluated with respect to reliability in conjunction to communication energy efficiency. Further, the proposed game-theoretic model sets the stage for deriving practical distributed query routing algorithms that are reliable and energy-efficient from a sensor-centric point of view.

### 2.2.2 Technical Approach

We now describe our technical approach for obtaining optimal length and energy-efficient routing paths in energy-constrained sensor networks. In Section 2.2.2.1, we derive analytical metrics labeled path weakness for evaluating the quality of different routing paths and describe inapproximability results for obtaining paths of bounded weakness. We use this metric to develop a heuristic for obtaining strong paths and compare the path weakness of our heuristic with routing paths obtained via well known routing algorithms. Finally, in Section 2.2.2.2, we describe how reverse directional flooding and energy depletion indicators can be used to develop routing protocols that dissipate energy equitable across the nodes in the network. We describe two different routing protocols and illustrate the improvement in node/network lifetime using these proctocols versus using some well-known georgraphic routing protocols.

#### 2.2.2.1 Quality of Routing: Analytical Model and Routing Heuristics

We now consider the following fundamental performance issue: How do we evaluate the sub-optimality of routing paths in sensor networks: Let $\mathcal{P}$ be any path from the source sensor $s_r$ to the sink node $s_q$. Consider any node $s_i$ on $\mathcal{P}$ with ancestors $\{s_r, \ldots, s_{i-1}\}$. Let $\hat{\mathcal{P}}_{iq}$ be the optimal Reliable Query Routing (RQR) path for routing information of value $\mathcal{V}_i$ (i.e., the expected value under any benefit model) to $s_q$ from $s_i$ in the subgraph $G\backslash\{s_r, \ldots, s_{i-1}\}$, assuming such a path exists. Thus $\hat{\mathcal{P}}_{iq}$ represents the best that node $s_i$ can do, given the links already established by nodes $s_r, \ldots, s_{i-1}$ **and** assuming optimal behavior from nodes $s_i$ onward, downstream. Define the *node weakness* of $s_i$ in path $\mathcal{P}$ as

$$\Delta_i(\mathcal{P}) = \Pi_i(\hat{\mathcal{P}}_{iq}) - \Pi_i(\mathcal{P}).$$

$\Delta_i(\mathcal{P})$ represents the payoff deviation for $s_i$ under the given strategy profile (path) $\mathcal{P}$. A positive node weakness represents the fact that $\mathcal{P}$ is suboptimal for $s_i$ while a negative one indicates that $s_i$ is benefiting more from this path (at the expense of some other sensor). $\Pi_i(\hat{\mathcal{P}}_{iq}) = 0$ if no optimal path from $s_i$ exists (for example, all of $s_i$'s neighbors might have very high communication/participation costs and cannot participate in any path). Note that $\Pi_i(\mathcal{P})$ can take on any value. We now define the following metrics for evaluating the suboptimality of routing paths:

1. *Path Weakness*: $\overline{\Delta}(\mathcal{P}) = \max_i \Delta_i(\mathcal{P})$.

   $\overline{\Delta}(\mathcal{P})$ identifies the maximum degree to which a node on the current path can gain by making a different strategy choice. The weakness metric embodies the idea that a path is only as good as its weakest node and allows us to rank the 'vulnerability' of different paths.

2. *Weakness Differential* :
   $\widetilde{\Delta}(\mathcal{P}) = \max_i \Delta_i(\mathcal{P}) - \min_i \Delta_i(\mathcal{P})$.

   While the path weakness metric highlights only the worst-off node, this describes the disparity between the worst-off node (the one most likely to deviate to a new strategy choice) and the best-off node, under the current outcome of the routing game $\mathcal{P}$. A small weakness differential value provides some indication of the fairness of the given path.

**Observation 1** $\{\overline{\Delta}(\mathcal{P}), \widetilde{\Delta}(\mathcal{P})\} = 0$ *if and only if* $\mathcal{P}$ *is the Nash equilibrium (optimal) path of the game and positive for all non-optimal paths.*

Thus paths with low weakness and weakness differential values are closer to the optimal and hence preferable. Note that the two weakness metrics can be similarly defined for data-aggregation trees. Given a sensor on any tree $\mathcal{T}$, its weakness can be calculated as its payoff deviation from the optimal tree that would have been obtained, given the expected value at that sensor along with the distribution of values in the remaining nodes in the graph.

**Inapproximability of RQR-Path with Bounded Weakness**

Next we compute bounds for finding paths with low weakness. We will show that there exist networks where it is not easy to find paths of bounded weakness or differential by constructing a specific instance whose best suboptimal paths satisfy certain weakness characteristics.

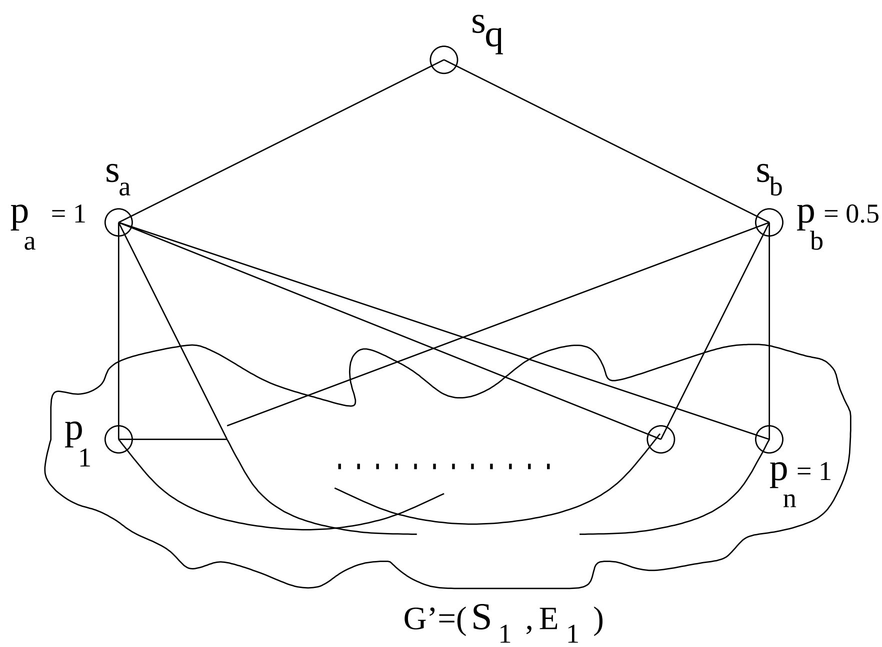



Figure 1: Network illustrating inapproximabilty of path weakness metrics.

Consider an arbitrary sensor network $G = (S, E)$ as shown in Fig. 2 with the following parameters: The vertex set $S$ is the union of vertex set $S_1$ with nodes $s_a$, $s_b$ and $s_q$. $G' = (S_1, E_1)$ is an arbitrary network, where $|S_1 = \{s_1, \ldots, s_n\}|$. $s_1$ contains information of value $v_r$ to be routed to $s_q$. The edge set $E$ for $S$ is the union of disjoint edge sets $E_1$, $E_2 = \{(s_a, s_i)\} \bigcup \{(s_b, s_i)\}, \forall s_i \in S_1$, $E_3 = (s_a, s_q)$ and $E_4 = (s_b, s_q)$. Participation costs are set to zero. Communication costs are fixed and represented by the following edge costs–edges in $E_2$ cost $\epsilon$, edge $E_3$ costs $v_r - \epsilon$ and edge $E_3$ costs $\frac{v_r}{2} - \epsilon$, where $\epsilon < \frac{v_r}{4}$. The node success probabilities are $P(s_i) = 1$ forall $s_i \in S_1$, $P(s_a) = 1$ and $P(s_b) = \frac{1}{2}$.

We now look at the optimal strategy choices for nodes in $G$ on any path from $s_r$ to $s_q$, under benefit model II. The analysis for benefit model I is very similar and hence omitted. Note that $s_q$ is reachable only through $s_a$ and $s_b$. Any path to $s_q$ that does not contain $s_b$ provides a benefit of $v_r$ to all nodes on the path. All other paths provide a benefit of $\frac{v_r}{2}$ to all nodes on the path. Therefore any path to $s_q$ via $s_a$ not involving $s_b$ provides the maximum payoff of $v_r - \epsilon$ to nodes in $S_1$ on that path and a payoff of $\epsilon$ to $s_a$. $s_a$ gets a higher payoff if it is an ancestor of $s_b$ on any path. Thus if $s_a$ is visited before $s_b$, it will prefer to link to any non-visited node in $S_1$ instead of linking directly to $s_q$. This path will eventually lead to $s_q$ via $s_b$ and provide a payoff of $\frac{v_r}{2} - \epsilon$

to all nodes on that path except $s_b$ and a payoff of $\epsilon$ to $s_b$. Note however that if $s_b$ is visited first (before $s_a$) it can only link directly to $s_q$ since all other paths to $s_q$ via $s_a$ yield a negative payoff for $s_a$ and hence are suboptimal.

Consider the following four paths: $\mathcal{P}_1 = (s_1, s_a, s_q)$, $\mathcal{P}_2 = (s_1, s_a, s_i, s_b, s_q)$ for any $s_i \in S_1$, $\mathcal{P}_3 = (s_1, s_b, s_q)$, and $\mathcal{P}_4 = (s_1, \ldots, s_n, s_a, s_q)$ consisting of a Hamiltonian path $\mathcal{H} = (s_1, \ldots, s_n)$ in $G'$ followed by $s_a$ and $s_q$.

Assume that $\mathcal{H}$ exists in $G'$. If so, we can easily show the following node weakness values for each path:

$$\begin{aligned}
\mathcal{P}_1: &\quad \Delta_{s_1}(\mathcal{P}_1) = 0, \quad \Delta_{s_a}(\mathcal{P}_1) = \frac{v_r}{2} - 2\epsilon && (1)\\
\mathcal{P}_2: &\quad \Delta_{s_1}(\mathcal{P}_2) = \tfrac{v_r}{2}, \quad \Delta_{s_a}(\mathcal{P}_2) = 0 \\
&\quad \Delta_{s_i}(\mathcal{P}_2) = 0, \quad \Delta_{s_b}(\mathcal{P}_2) = 0 && (2)\\
\mathcal{P}_3: &\quad \Delta_{s_1}(\mathcal{P}_3) = \tfrac{v_r}{2}, \quad \Delta_{s_b}(\mathcal{P}_3) = 0 && (3)\\
\mathcal{P}_4: &\quad \Delta_{s_i}(\mathcal{P}_4) = 0 \forall i, \quad \Delta_{s_a}(\mathcal{P}_4) = 0 && (4)
\end{aligned}$$

We do not consider other paths that consist of visits to nodes in $S_1$ interleaved between visits to $s_a$ and $s_b$ or paths that visit $s_b$ before $s_a$ as they can be shown to have the same weakness characteristics as the above paths.

We can now conclude the following path weakness metrics:

$$\begin{aligned}
\overline{\Delta}(\mathcal{P}_1) = \frac{v_r}{2} - 2\epsilon, \quad \overline{\Delta}(\mathcal{P}_2) = \tfrac{v_r}{2}, \quad \overline{\Delta}(\mathcal{P}_3) = \frac{v_r}{2} && (5)\\
\widetilde{\Delta}(\mathcal{P}_1) = \frac{v_r}{2} - 2\epsilon, \quad \widetilde{\Delta}(\mathcal{P}_2) = \tfrac{v_r}{2}, \quad \widetilde{\Delta}(\mathcal{P}_3) = \frac{v_r}{2} && (6)
\end{aligned}$$

Finally, we have,

$$\overline{\Delta}(\mathcal{P}_4) = 0 \qquad \widetilde{\Delta}(\mathcal{P}_4) = 0 \tag{7}$$

Since $G'$ is an arbitrary subgraph of $G$, the above result implies the existence of infinitely many graphs without any suboptimal paths of weakness or weakness differential bounded by $(\frac{v_r}{2} - \epsilon)$. A similar analysis can be carried out for benefit model I. We have the following result.

**Theorem 1** *Under both benefit models I and II, there exists no polynomial time algorithm to compute approximately optimal RQR paths of weakness or differential weakness less than* $(\frac{v_r}{2} - \epsilon)$ *unless* $P = NP$.

**Proof:** Let $\mathcal{A}$ be an algorithm that outputs a path with weakness less than $\frac{v_r}{2} - \epsilon$ in polynomial time. For the given $\epsilon$, choose $G$ with probabilities and costs as described above. We can then use $\mathcal{A}$ as a decision algorithm to solve the Hamiltonian path problem in $G'$. If a Hamiltonian path exists in $G'$, it is the only path with weakness less than $\frac{v_r}{2} - \epsilon$ in $G$ and will therefore be output by $\mathcal{A}$. Algorithm $\mathcal{A}$ will return some other path in $G$ (which can be verified as non Hamiltonian in polynomial time) only if no Hamiltonian path exists in $G'$. Thus $\mathcal{A}$ is a polynomial time decision algorithm for solving the Hamiltonian path problem. This is impossible unless $P = NP$. ■

**Path Weakness Heuristics**

Theorem 1 indicates the infeasibility of finding approximately optimal RQR paths of small weakness/differential in arbitrary sensor networks. Here we present some easy to compute heuristics based on a fair-team version of the RQR game (called FTRQR), for finding approximate RQR paths. Simulation results presented in the next subsection verify that the FTRQR heuristic has low path weakness and compares favorably with other standard routing algorithms.

Define a 'team' version of the RQR game as one in which all nodes on the path share the payoff of the worst-off node on it. Rather than maximizing individual payoffs as in the original game, nodes in the team model compromize by selecting next-neighbors that maximize the shared least possible payoff. Formally, the payoffs to nodes in the network under strategy choice $l$ leading to path $\mathcal{P}$ are as follows:

$$\Pi_i(l) = \begin{cases} R(\mathcal{P})(\sum_i v_i) - \max\limits_{(s_i,s_j)\in\mathcal{P}} (c_{ij} + CP_i) & \text{if } s_i \in \mathcal{P} \\ \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where $v_i$ is the value of information at node $s_i$ and $R(\mathcal{P})$ is the reliability of path $\mathcal{P}$ from $s_r$ to $s_q$ formed under strategy choice $l$ . The Nash equilibrium of this team game is the path from source to destination containing the node with the maximum minimum cost-reliability trade-off over all paths. In case of multiple equilibria, the path with highest reliability is selected.

While the above heuristic finds the path maximizing the payoff of the lowest payoff node, the disparity in individual payoffs (as defined in the original RQR game) between the best and worst-off nodes on the equilibrium path can be considerable. Thus the node weakness of individual sensors on this path can also differ considerably and the path weakness as well as the differential weakness might be high. Therefore a heuristic that minimizes the differential path weakness (ie. differences in individual node payoffs) of the equilibrium path will lead to 1) more equitable sensor energy expenditures and 2) should potentially decrease the path weakness. However such a heurstic might lead to less reliable paths. Since achieving energy fairness at the cost of reliability is against the overall routing objective, hence the new equilibrium should also satisfy the original team notion of the RQR game. We therefore propose a composite heuristic labeled fair team-RQR (FTRQR) as follows:

$$\Pi_i(l) = \begin{cases} (R(\mathcal{P})(\sum_i v_i) - \max\limits_{(s_i,s_j)\in\mathcal{P}} (c_{ij} + CP_i)) \quad + \\ \min\left(\beta, \frac{1}{\max\limits_{(s_i,s_j)\in\mathcal{P}}(c_{ij}+CP_i) - \min\limits_{(s_k,s_l)\in\mathcal{P}}(c_{kl}+CP_k)}\right) \\ \\ \qquad\qquad\qquad\qquad\qquad\qquad \text{if } s_i \in \mathcal{P} \\ 0 \qquad\qquad\qquad\qquad\qquad \text{otherwise} \end{cases} \tag{9}$$

The first component above addresses the team payoff aspect while the second component attempts to ensure that individual payoffs are as close to the team payoff as possible. The $\beta$ parameter limits the impact of the payoff fairness criterion. Naturally, a weighted version of the two components is also possible.

The FTRQR heuristic bears some similarity to the standard bottleneck shortest path problem, which minimizes the cost of the longest edge on the path from the source to the destination node. The optimal FTRQR path can be interpreted as the bottleneck path to node $s_q$ with the highest path reliability and lowest cost differential.

### 2.2.2.2 Length-Energy-Constrained Routing Protocols

With current technology, communication energy costs typically outweigh processing and sensing costs in sensor networks. Thus the longevity of a sensor node depends heavily on the number of routing paths it participates in. Improperly chosen routing paths will lead to uneven energy consumption across sensors; highly non-uniform residual node energy might also expedite network partition. Therefore routing protocols must be designed to dissipate energy equitably over sensors.

One possible approach is to prevent low energy nodes from taking part in a route as long as they are energy-deficient relative to their neighbors. However, a route that focuses only on energy efficiency may be undesirably long (in terms of hop count) since the lowest energy-cost path need not be the shortest. Longer paths will result in energy depletion at more sensors while also increasing delay. While there are several existing protocols in the literature that focus exclusively on either of these issues, there is no unified analytical model that explicitly considers routing under both the constraints of energy efficiency and path length.

We model sensors as intelligent agents and propose a game theoretic paradigm for solving the problem of finding energy-optimal routing paths with bounded path length. The equilibrium point(s) of the routing game define the optimal routing path. We then define a team version of this routing game and propose a distributed nearly-stateless leader to leader energy efficient routing protocol that finds the optimal route. We now formally define our analytical model and formulate the routing game.

Let $S = \{s_1, s_2, \ldots, s_n\}$ be the set of sensors in the sensor network participating in the routing game. Let $L_1$ and $L_2$ be a pair of leader nodes using sensors in $S$ as intermediaries[1]. Data packets are to be routed from $L_1$ to $L_2$ through an optimally chosen set $S' \subset S$ of intermediate nodes by forming communication links. Note that we do not consider multicast communication between sets of leader nodes in this paper.

**Strategies:** Each node's strategy is a binary vector $l_i = (l_{i1}, l_{i2}, ...., l_{ii-1}, l_{ii+1}, ..., l_{in})$, where $l_{ij} = 1$ ($l_{ij} = 0$) represents sensor $s_i$'s choice of sending/not sending a data packet to sensor $s_j$. Since a sensor typically relays a received data packet to only one neighbor, we assume that a node forms only one link for a given source and destination pair of leader nodes. In general, a sensor node can be modeled as having a mixed strategy, i.e., the $l_{ij}$'s are chosen from some probability distribution. However, in this paper we restrict the strategy space of sensors to only pure strategies. Furthermore, in order to eliminate some trivial equilibria, each sensor's strategy is non-empty and strategies resulting in a node linking to its ancestors (i.e. routing loops) are disallowed. Consequently, the strategy space of each sensor $s_i$ is such that Prob. $[l_{ij} = 1] = 1$ for exactly one sensor $s_j$ and Prob. $[l_{ij} = 1] = 0$ for all other sensors, such that no routing loops are formed.

**Payoffs:** Let $l = l_1 \times l_2 \times \ldots \times l_n$ be a strategy in the routing game resulting in a route $\mathcal{P}$ from source to destination leader node. Each sensor on $\mathcal{P}$ derives a payoff from participating in this route. The payoff of a sensor $s_i$ which links to node $s_j$ in $\mathcal{P}$ is then defined as:

$$\pi_i(l) = E_j - \xi L(\mathcal{P}) \tag{10}$$

where $E_j$ is the residual energy level of node $s_j$ and $L(\mathcal{P})$ the length of routing path $\mathcal{P}$. $E_j$ represents a benefit to $s_i$, thus inducing it to forward data packets to higher energy neighbors. The parameter $\xi$ represents the proportion of path length costs that are borne by sensor $s_i$. Choosing $\xi$ as a positive constant or proportional to path length will inhibit the formation of longer routing paths. Conversely, setting $\xi$ zero or inversely proportional to path lengths will favor the formation of paths through high-energy nodes. We choose $xi$ as a non-zero positive constant for this routing

[1] In general, sensors in $S$ will be simultaneously participating in routing paths between several such pairs.

game. Thus each sensor will forward packets to its maximal energy neighbor in such a way that the length of the path formed is bounded. This model encapsulates the process of decentralized route formation by making sensor nodes cooperate to achieve a joint goal (shorter routing paths) while optimizing their individual benefits.

A Nash equilibrium of this game corresponds to the path in which all participating sensors have chosen their best-response strategy, i.e., the one that yields the highest possible payoff given the strategies of other nodes. This equilibrium path is the optimal Length Energy-Constrained (LEC) route in the sensor network for the given leader pair. Note that the process of determining the LEC route requires each node to determine the optimal paths formed by each of its possible successors on receiving its data. The node then selects as next neighbor that node, the optimal path through which incurs the highest payoff.

**Theorem 2** *Let $\hat{\mathcal{P}}$ be the optimal LEC route for a pair of source and destination leader nodes in an arbitrary sensor network. Computing $\hat{\mathcal{P}}$ is NP-Hard.*

**Theorem 3** *Let $S$ be any sensor network in which sensor are restricted to following a* **geographic routing** *regime. In other words, the strategy space of each sensor includes only those neighbors geographically nearer to the destination than itself. Then $\hat{\mathcal{P}}$ can be computed in polynomial time in a distributed manner.*

### Distributed Protocol Implementation

We describe three different protocols for finding an energy-efficient route and balancing energy across the sensornet as a concomitant side-effect. This section is divided into three subsections, each subsection describing a protocol.

*A. Length-energy Constrained Geographic Routing Protocol (LCGR)*

This protocol is a distributed implementation of the optimal LEC routing game. In this protocol, each node calculates its highest payoff according to the model described above and form the optimal path. Since node energy levels are changing continuously in a sensor network due to sensing, processing and routing operations, both the optimal path and the threshold need to be recomputed periodically. Thus the proposed protocol operates in two different phases: data transmission and path determination. During the path determination phase, the calculation of the optimal path and the threshold value takes place. The protocol is described below in details:

*A.1 Data Transmission Phase*

During this phase, data packets are transmitted from one leader node $L_1$ to the other node leader node $L_2$ through the optimal path (with least energy weakness). Each data packet also potentially collects information about the energy consumption en route, by keeping track of residual energy levels of nodes on the path. When energy levels of a given critical number of nodes fall below a certain threshold, the data transmission phase ends and the new optimal path determination phase begins.

The fundamental steps of the data transmission phase are as follows:

- Each data packet is marked by the source leader node with the geographical position of the destination node and with a threshold value $th$. Each data packet contains a special $n$-bit Energy Depletion Indicator (EDI) field, where $n <<$ packet size.

- Each sensor node receiving a data packet determines whether its energy level has fallen below the threshold $th$. If so, and the EDI field in the data packet is not exhausted, the node sets a

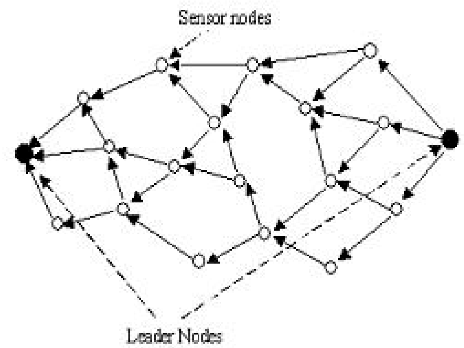



Figure 2: Reverse Directional Flooding

single bit in the EDI field. Then it forwards the packet to the best next-hop neighbor according to its routing table. We assume that before the network starts any activity, all ordinary 'non-leader' sensor nodes have the same energy level. Therefore, during the first data transmission phase, the best next-hop neighbor of a node is the one which is geographically nearest to the destination leader node. In all other phases, the routing table is updated according to the optimal LEC path calculation.

- If the receiver leader node gets a data packet with all $n$ bits in the EDI field set to 1, it triggers a new optimal path selection procedure. Note that the length of the EDI field is an emperical value that must be chosen carefully, as discussed in section 5.2.

**Calculation of the Threshold Value**

The threshold value $th$ plays a very important role in the data transmission phase since it is used to provide an approximate indication that the current optimal path has become obsolete. Intuitively, $th$ must be a function of the current residual node energy levels in the network. In this paper, we use the following function for all three protocols:

$$th = \beta \;\; E_{min} \tag{11}$$

where $0 < \beta < 1$ and $E_{min}$ is the maximum of minimum node energy levels on all geographic routing paths to the destination $L_2$. Since $E_{min}$ changes with time, the threshold is recalculated in each path determination phase, consistent with the current energy distribution across the network.
*A.2 Path Determination Phase:*

This phase begins when the destination leader node receives critical EDI information and ends when the sending leader node has updated its routing table and recalculated the threshold value. The principle steps are as follows:

- The destination leader node $L_2$ triggers this phase by flooding the network with control packets along the geographic direction of the source leader node $L_1$ (Figure 2). Note that this *reverse directional flooding* occurs in the direction opposite to that of data transfer.

- Each node forwards *exactly one* control packet to all its neighbors in the geographic direction of $L_1$. Each control packet contains three fields: the given node's residual energy level, a length field $L(P)$ that indicates the length of the current *optimal* partial path from that node to $L_2$ and a max-min energy field $EM_p$ that indicates the maximum of the minimum node energy levels on all partial paths to $L_2$ originating at the given node. $L(P)$ is calculated in the iterative way described below.

- On receiving the first control packet, each node sets a timer for a prefixed interval $T$. This time-period should be large enough for the node to receive future control packets from all or most of its upstream neighbors (corresponding to different partial paths from the upstream nodes to $L_2$), but not so large as to cause high delays. With each arriving control packet, the node calculates, updates and stores the highest $E - \xi L(P)$ value seen so far, where $E$ and $L(P)$ are the residual energy level and optimal partial path length to $L_2$ from that upstream neighbor. It also updates and stores the highest $EM_p$ value seen so far. *However, if its own energy level $E_i$ is lower than all these $EM_p$ values, it stores $E_i$.* With each control packet, the given node also updates its routing table for destination $L_2$ to point to the node from which it will receive the highest payoff. Note that the choice of this optimal neighbor is independent of partial path lengths from $L_1$ to the given node and is in fact the upstream node with the highest $E - \xi L(P)$ value .

- When its timer expires, this node creates a control packet with the $L(P)$ field set as the length of the current optimal partial path to $L_2$ (via the highest payoff neighbor). The control packet also contains the current $EM_p$ and residual energy fields and is forwarded to all its neighbors in the geographic direction of $L_1$. Control packets arriving after the timer expires are discarded.

- Eventually, $L_1$ begins receiving control packets and sets its timer. Its value of $T$ can be determined in many ways depending on the specific requirements of applications. In this paper, we calculate $T$ to ensure that most of the paths from $L_1$ to $L_2$ are included in the optimality calculations. If $(D_{max})$ is the maximum transmission delay between two nodes, the value of $T$ is determined as $(MINHOP * D_{max})$, where $MINHOP$ is an estimate of the shortest path from $L_1$ to $L_2$. This value can be estimated a priori using GPSR routing, before the first data transmission phase. Note that the given value of $T$ allows control packets from paths up to twice the length of the shortest path to be forwarded to $L_1$. Also note that $D_{max}$ is a function of the specific MAC-layer protocol being implemented in the sensor network. Finally, when the timer expires at $L_1$, it sets its routing table and calculates the new threshold value $th$ using $E_{min}$ as the highest received $EM_p$ value. The next data transmission phase can now begin.

*B. Max-min Energy-constrained Geographic Routing Protocol (MEGR)*

For comparative purposes with LCGR, we consider an alternative protocol implementing a simplified 'team' version of the original LEC routing game. MEGR has the same overhead as LCGR but computes optimal paths using the following team path heuristic: each node on a path shares the payoff of the worst-off node on it. Formally, let $\mathcal{L}$ be the set of all distinct paths from a particular source and destination leader pair. Let $E_{min}(\mathcal{P})$ be the smallest residual energy value on path $\mathcal{P}$. Then the equilibrium path of the team LEC game is defined as:

$$\hat{P} = \text{argmax}_{\mathcal{P}\in\mathcal{L}}(E_{min}(\mathcal{P}) - \xi \quad |\mathcal{P}|) \tag{12}$$

For simplicity, we set $\xi$ to zero. However, the protocol can be easily implemented for non-zero values of $\xi$. We interpret the optimal path under this condition as follows: Given any path $\mathcal{P}$, the durability of the path is inversely proportional to $E_{min}(\mathcal{P})$. A path with lower average energy but higher minimum energy should last longer than a route with the opposite attributes since the least energy node is the first to terminate and make that route obsolete. The inverse of the minimum node energy on a given path reflects the *energy weakness* of the path. Thus MEGR will select an optimal path with the least energy weakness. The protocol is implemented in the same manner as LCGR with data transmission and path determination phases.

#### 2.2.2.3 Comparison with Current Technology

Current technology on routing in sensor networks focuses primarily on energy-constrained routing by emphasizing the untethered and unattended nature of sensor nodes. Since sensor networks can be deployed in hazardous environments, we consider the problem of routing under the additional constraint of node survivability. Also, our model is the first to consider routing in the context of optimizing individual sensor costs, while taking network wide benefits into account. We therefore classify our approach as sensor-centric, which distinguishes it from other existing models. We successfully define a new routing paradigm that explicitly optimizes over both dimensions, i.e., a new model for reliable energy-constrained routing in sensor networks that takes into account all the major constraints of sensor operation as opposed to previous models in this field, which were limited in scope and analysis. Our proposed length-energy constrained protocols differ from (and are superior to, as shown in the results section) existing protocols in the literature in the following respects:

1. Unlike other network lifetime maximization protocols that require global information on current data/packet flow rates from each sensor to sink(s), our protocol utilizes very limited network state information and is thus easily implementable.

2. Energy being a critical resource in sensor networks, depleted regions (i.e regions with low residual node energies) must be detected and bypassed by routing paths as quickly as possible. This is analogous to congestion in wired networks. We propose a new technique for indicating the onset of energy depletion in regions by using energy depletion indicators. This is used in conjunction with the energy weakness metric in our protocol to ensure energy-balanced routing.

3. Geographic sensornet routing algorithms such as GPSR and GEAR employ elegant neighbor selection procedures using only local network information. These mechanisms enhance energy savings at individual sensor nodes and are easy to implement. However due to their predominantly local nature, there are situations in which these protocols will be slow to adapt to changing energy distributions in the network. For example, consider a region in a sensornet that is intersected by multiple routes and thus has higher energy depletion rates. While GEAR is likely to take a considerable amount of time to avoid this region through localized rerouting, our protocol, with its energy depletion indicator algorithm, will quickly detect such regions and establish new bypass routes.

4. In several traditional sensornet routing protocols, a single routing path (typically, the least energy path) is utilized continuously until a node's energy is completely exhausted. While the motivation behind this approach is to save energy consumption at individual sensor nodes, this might lead to unintended consequences such as the expedited partition of the network. Our protocol overcomes this drawback by selecting new length-energy-constrained routing paths periodically.

## 3. Technical Report

This technical report section is delineated into three parts. We first summarize our technical progress at the end of the project period. Next we describe major results obtained and finally, we discuss publication and other outcomes related to this project.

### 3.1 Summary Technical Accomplishments

We have three major technical accomplishments in this project:

1. We have developed three new geographical routing protocols for length-energy-constrained routing in sensor networks using the concept of reverse directional flooding and energy depletion indicators. We have shown that implementation of these protocols will lead to improved network lifetime as compared to several existing geographic routing algorithms.

2. We have developed sensor-centric quality of routing metrics (labeled path weakness) and determined fundamental approximation limits on finding routing paths with bounded weakness.

3. We have developed a software test-bed for evaluating many different routing protocols. Our test-bed is based on a novel simulator based on ns-2 and our modifications using Tcl and C++. The simulator can simulate a sensor network of any size and deployment topology and accounts for actual node energy-consumptions under any given routing protocol. Nodes contend for the medium using a standardized TDMA scheme with the given routing protocol overlaid on this MAC layer. Nodes can be programmed to have different duty cycles (sleep, awake) in order to reflect real-life network operation at multiple network layers (not just routing layer). However, we have used our simulator to primarily test routing protocol energy metrics. The simulator will be available for public dissemination.

**3.2 Major Results** We now describe in detail our major results for evaluating the quality of routing in wireless sensor networks along with our novel energy-efficient geographic routing protocols.

#### 3.2.1 Experimental results on Quality of Routing:

We have compared the path weakness characteristics of several standard routing algorithms along with the FTRQR team-game based heuristic. We have used the following setup in our simulations: We consider routing from a single source containing information of value $v_r = 1$ to the sink on a 20-node random graph with 30% edge density, a uniform node survival probability and random edge costs from a given parameter range. Edge costs are assumed static and node participation costs are set to 0. For each set of node success probabilities and edge costs, we evaluate the path weakness for routing paths under benefit model II from 15 source and destination pairs generated using the 1) The FTRQR heuristic, 2) the Most Reliable Path (MRP), 3) the Cheapest Next-Node Path (CNP) and, 4) the Overall Least-Cost Path (MCP). (2) and (4) can be obtained using Djikstra's algorithm. The CNP is obtained by sequentially following the cheapest link out of each node that leads to the destination. For simplicity, whenever the algorithms produce paths with negative payoffs for some nodes, we set the path weakness value to 1.

**Analysis:**

Our simulation results are illustrated in Figures 3–6. We are interested in finding ranges of costs and node success probabilities in which the different standard algorithms perform well. Initially,

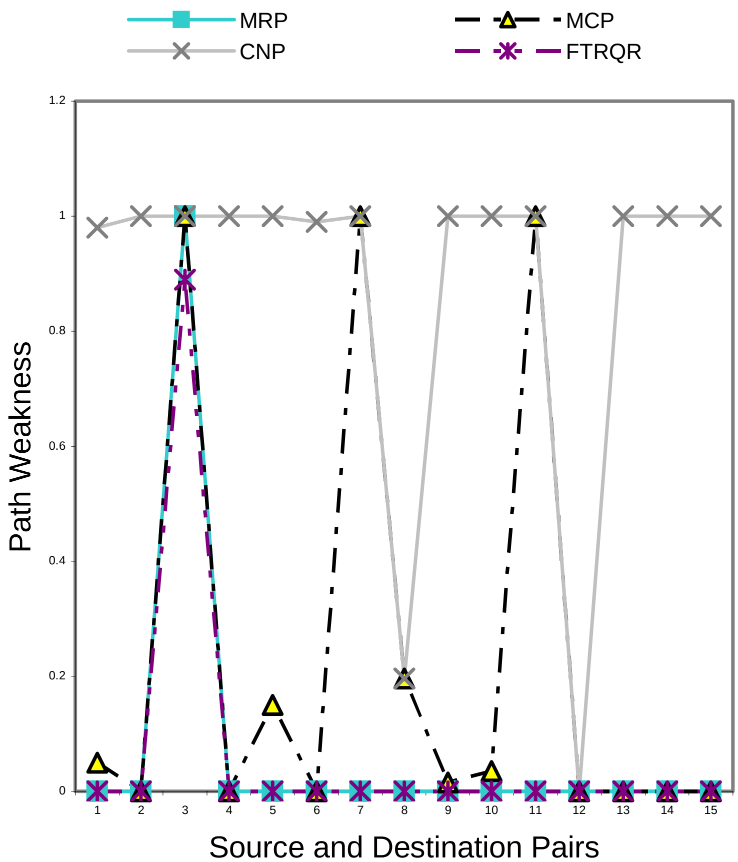



Figure 3: $p = 0.5, c \leq 0.06$.

we model more unreliable and costly networks with low success probabilities and relatively high edge costs.

In Fig. 3, we keep the node success probability at 0.5 and the maximum edge cost at 0.06. This restricts the length of the optimal path since edge costs soon outweigh reliability benefits for nodes on long paths. In this case, MRP, the shortest path, always coincides with the optimal path despite the low node success probability. FTRQR, because of its reliability component, also has very low weakness and coincides with the optimal in most cases. However, the cost based algorithms, especially CNP have very high weakness since they result in much longer paths from source to destination. (Typically, CNP will result in the longest path since it minimizes individual node costs without regard to reliabilities).

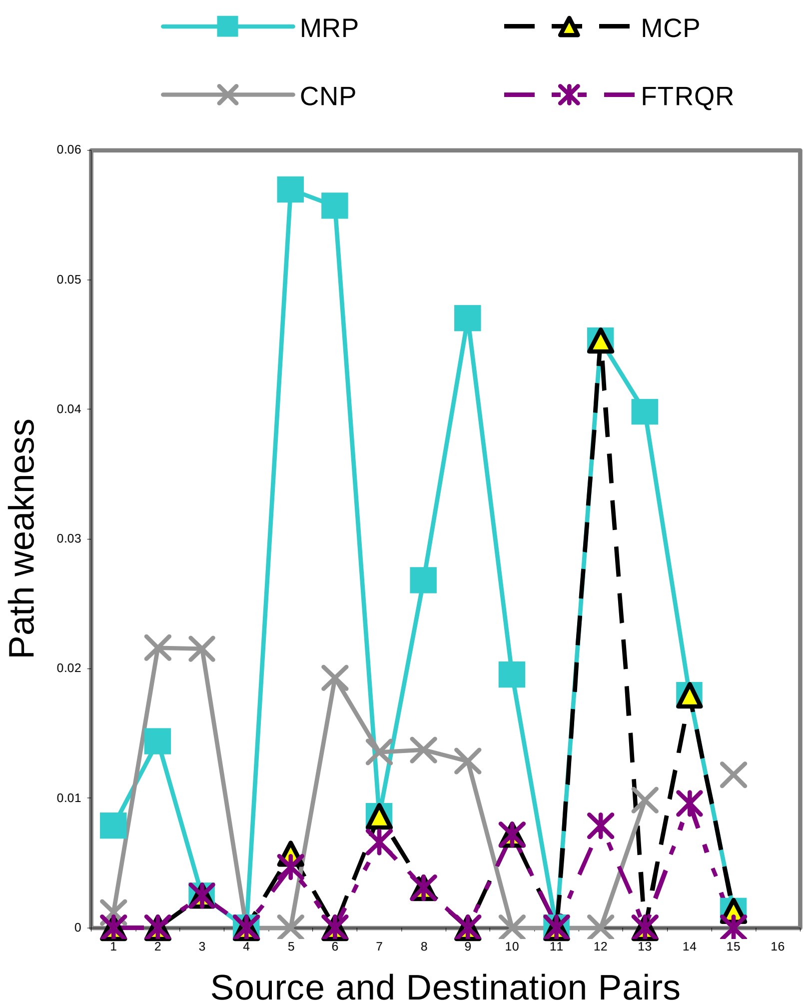



Figure 4: $p = 0.995, c \leq 0.06$.

In Fig. 4, we increase the node success probability dramatically to 0.995 keeping the maximum edge cost the same at 0.06. In this case, longer optimal paths are possible and routes based solely on maximizing reliability should not perform too well. This is clearly illustrated by the relatively higher path weakness values for MRP. Conversely, the CNP metric now (as compared to Fig. 1) has much lower weakness. Since nodes are more reliable now, the longer paths generated by CNP are not too suboptimal. However, FTRQR outperforms CNP since it combines reliability as well as cost to a limited extent. Note that the MCP heuristic also does surprisingly well, even though it is exclusively based on minimizing total edge cost. Minimizing total edge costs in many cases (with low maximum edge costs) will yield *short paths* with low edge cost variation on the path. Since all nodes in our simulations are set to have the same success probabilities, the reliability of the MCP paths will be quite high along with low individual edge costs. Hence MCP performs well. Note that this feature of high reliability with low costs is shared by the FTRQR heuristic and this is why both heuristics perform well. However, we suspect that when node probabilities are non-uniform, MCP will perform poorly since MCP paths are likely to have low reliabilities whereas the FTRQR heuristic trades off reliability and costs and should have low weakness even in such cases.

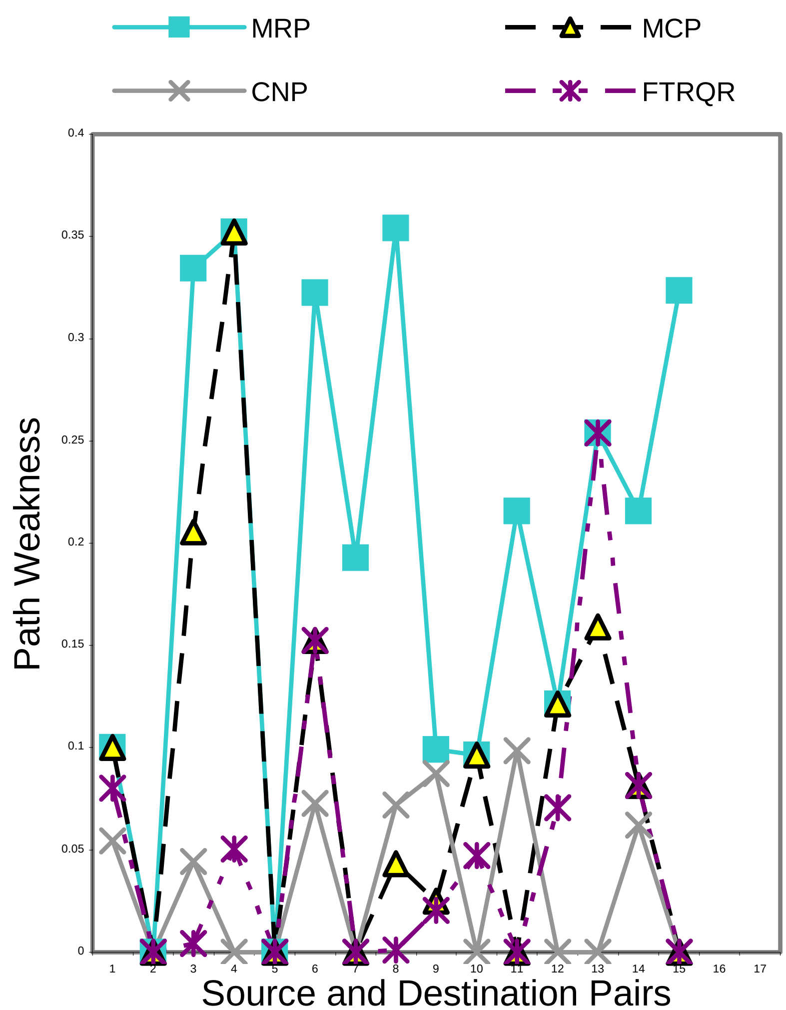



Figure 5: $p = 0.98, c \leq 0.04$.

In Fig. 5 we decrease both maximum edge costs and probabilities slightly. The path weakness of MCP increases slightly (lower node success probabilities lead to lower MCP path reliabilities). MCP is slightly outperformed by FTRQR which conforms to the above intuition.

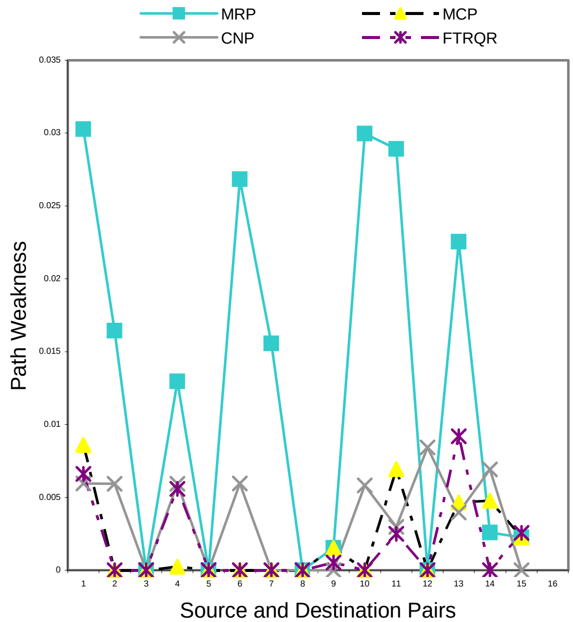



Figure 6: $p = 0.999, c \leq 0.029$.

Finally, in Fig. 6, we consider a highly reliable network with very low edge costs. Now optimal paths can have longer lengths without sacrificing reliability. Therefore CNP, which tends to have a longer length, has lower path weakness now. MRP has higher path weakness due the presence of large number of paths (including low individual edge cost paths) with high reliabilities. The FTRQR heuristic, which tradesoff path reliability and cost differences performs well as expected.

Based on these simulations, in summary, we can state that the sensor-centric paradigm works best in highly reliable yet low cost networks. For unreliable networks, using the MRP heuristic is preferable. When success probabilities are uniform or within a very narrow range along with low maximum edge costs, MCP is a good heuristic. CNP rarely produces paths of comparitively low weakness. The FTRQR heuristic performs quite well in most cases and has low path weakness as it inherits the reliability characteristics of MRP in unreliable networks and that of the cost optimizing algorithms in higly reliable networks

#### 3.2.2 Performance Evaluation of our Length-Energy Constrained (LEC) Routing Protocols:

The main objective of our LEC protocols is to gradually balance energy consumption across the network. To evaluate protocol performance, we use the following metrics which reflect dispersion or concentration of energy consumption across a sensornet.

- **Variance of energy level**: The variance of the energy levels of all the nodes is the primary

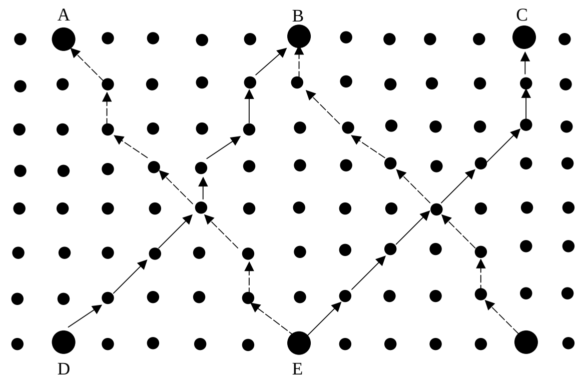
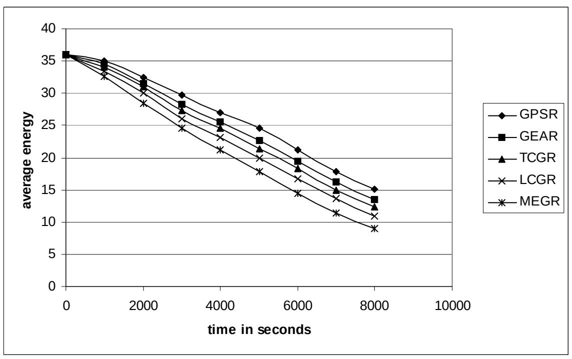
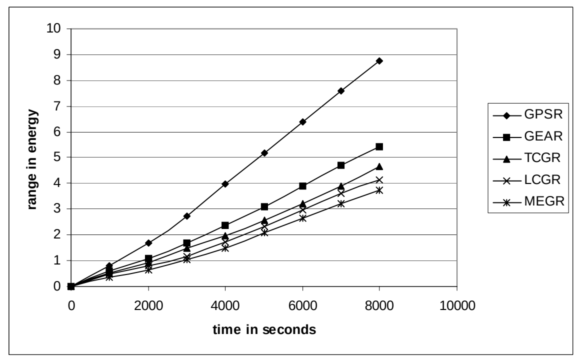



Figure 7: Simulation topology




(a) $Rate1$




(b) $Rate2$

Figure 8: Range of residual energy levels across the network

measure of dispersion. A high variance indicates higher energy consumption at some of the nodes compared to others.

- **Range of energy level**: This metric measures the difference between the energy levels of the maximum energy node and the minimum energy node over the whole network. A large value for this range is a result of unfair distribution of routing load among the nodes.

**Experimental Setup** In our simulation we have 100 nodes in a $1000 \times 1000$ meter area, with one node at each of the positions of the $10 \times 10$ square grid. Fig. 6 represents the mesh topology that we have used for evaluating our protocol. The whole network is divided into five clusters. There are two sensing areas in the regions under clusters A and B. Sensor data packets are generated from these sensing areas at a uniform rate. The leader nodes in each of the clusters A and B collect these packets and send them to the leader nodes of clusters C and D respectively via intermediate sensor nodes. Leader nodes C and D forward these packets to the sink node in cluster E. Each leader node selects the leader node which is geographically nearest to the sink for transmitting its received/sensed data. Leader to leader communication is accomplished through ordinary sensors. Reverse directional flooding is initiated when a leader node receives a sensor data packet indicating that at least *three* sensor nodes are close to the threshold $th$. A sender leader node sets $th$ to the new $\beta E_{min}$ obtained from the reverse flooding phase. We run the simulation

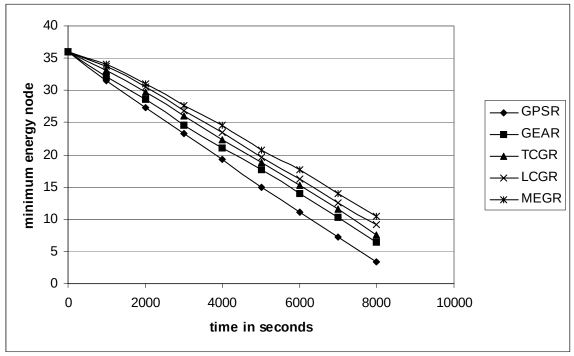



Figure 9: Variance in residual energy levels across the network

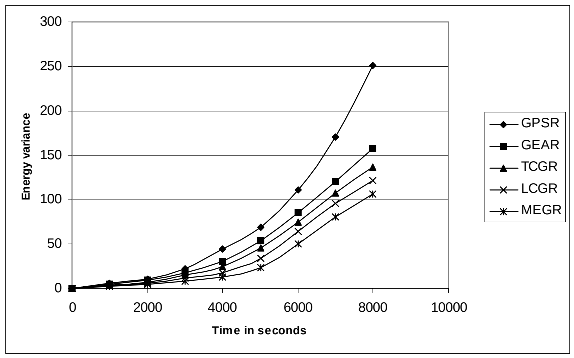



Figure 10: Minimum residual energy levels across the network

for 900 seconds and compare five protocols for energy efficiency: geographic shortest path routing (GPSR), GEAR and the proposed LEC protocols. The GPSR protocol uses the geographically shortest path for leader to leader communication. In GEAR, a node $N_i$ dynamically chooses its minimum cost neighbor for forwarding its packet, where costs are parametrically estimated as $c(N_i) = \alpha d(N_i) + (1 - \alpha)E(N_i)$. Here $d(N_i)$ and $E(N_i)$ are the neighborhood-normalized distance to destination and energy consumed at $N_i$ respectively. In our simulations, we compare the team LEC protocol for inter-leader comunication with GEAR using $\alpha = 0.5$.

**Results and Analysis**: We assume that before the network starts any activity, all ordinary sensor nodes have the same energy level. Therefore, in the very beginning, energy distribution is uniform across the network. When a network becomes active, the energy distribution across it gradually becomes non-uniform since nodes participating in a route inevitably consume more energy than other nodes. A protocol which uses a fixed route until one node in the route is completely drained of energy, ends up producing an energy distribution with high dispersion of energy levels. On the other hand, our proposed protocol tries to adapt to the dynamically changing energy distribution and gradually evens out the initial uneven energy distribution. Therefore, it is expected that the difference between the dispersion measures produced by our protocol and those produced by any protocol with fixed routing will increase with an increasing rate with time.

Results of our simulation comparing performance of our protocols with that of GEAR and GPSR are illustrated in Figures 8–10. In Figure 8(a) and 8(b), we present the difference in the ranges of node energy distributions across the network over time under the three protocols using two different traffic rates. In both the figures, the difference of the ranges rises very sharply indicating that our protocol yields lower range of energy distribution compared to that produced by the fixed route protocol as time proceeds. Moreover, with an increased traffic rate, our protocol produces a much better result compared to that of shortest path routing. This indicates that with heavy traffic, the energy distribution across the network become more uneven in a fixed route protocol since the load is heavier on a particular route. In this case, frequent change of routing path is very much useful in bringing uniformity to overall energy consumption.

Note that the energy range metric does not measure the number of sensor nodes that are being treated unfairly. Therefore in Fig. 9 we illustrate the variance of residual energy distribution produced by our protocols and that by GPSR and GEAR. The high variance of GPSR indicates that a significant number of sensor nodes are being treated unfairly with network traffic being concentrated at fewer nodes. This might expedite partition of the network due to energy depletion at critical nodes.

Fig. 10 illustrates how the difference between the minimum energy level produced by our protocols and that by GPSR and GEAR changes with time In both cases, the difference rises very sharply with time. With a higher value of $\beta$, the rise will be sharper because change of route is accomplished more frequently and therefore energy consumption will be more uniform under our protocol.

### 3.2.2 Publications

This project led to six journal and three conference publications and supported the education of one Ph. D student at LSU (Ms. Lydia Ray). One paper on sensor-centric quality of routing was presented at IEEE INFOCOM in April 2003, the premier networking conference. Another paper on our efficient length-energy constrained routing protocols was presented in Berlin in January 2004. Publication details are listed below.

**Journal Publications**

[J1] R. Kannan and S. S. Iyengar, "Game-Theoretic Models for Reliable Path-Length and Energy-Constrained Routing with Data Aggregation in Wireless Sensor Networks, IEEE Journal on Selected Areas of Communication, in press, 2004.

[J2] R. Kannan, S. Sarangi and S. S. Iyengar, "Sensor-Centric Energy-Constrained Reliable Query Routing for Wireless Sensor Networks,Journal of Parallel and Distributed Computing. July 2004.

[J3] R. Kannan, L. Ray , R. Kalidindi and S. S. Iyengar, " Threshold-Energy Constrained Routing Protocol for Sensor Networks,Sensor Letters, December 2003.

[J4] W. Ding, S.S. Iyengar, R. Kannan, W. Rummler, "Energy Equivalence Routing in Wireless Sensor Networks", Special issue on Wireless Sensor Networks in Journal of Microcomputers and Applications, in press, 2004.

[J5] Rajgopal Kannan, Ramaraju Kalidindi, S. S. Iyengar and V. Kumar, "Energy and Rate based MAC Protocol for Wireless Sensor Networks," ACM SIGMOD Record, Vol. 32 No. 4, pp. 60-65 (2003).

[J6] R. Kannan, S. Sarangi, S. Ray and S. S. Iyengar, " Minimal Sensor Integrity: Measuring the Vulnerability of Sensor grids," Information Processing Letters, Vol. 86, No. 1, pp. 49-55, 15 April 2003.

**Conference Publications**

[C1] R. Kannan, S. Sarangi, S. S. Iyengar and L. Ray, " Sensor-Centric Quality of Routing in Sensor Networks, IEEE INFOCOM 2003, San Francisco, CA April 2003.

[C2] R. Kannan, L. Ray, S. S. Iyengar, and R. Kalidindi," Max-Min Length-Energy-Constrained Routing in Wireless Sensor Networks," LNCS-Lecture Notes in Computer Science, Springer-Verlag, Vol 2920, ISBN=3-540-20825-9, pp. 234-249. (1st European Workshop on Wireless Sensor Networks, Jan 19-21, 2004).

[C3] R. Kalidindi, L. Ray, R. Kannan, and S. S. Iyengar," Distributed Energy-Aware MAC Protocol for Wireless Sensor Networks, in International Conference on Wireless Networks , Las Vegas, Nevada, June 2003.

## 4. Conclusions

We have shown that game theory offers a promising framework for modeling reliable length-energy constrained routing in sensor networks. We present two metrics for evaluating the quality of routing paths labeled path weakness and show the inapproximability of finding paths of bounded weakness in arbitrary sensor networks. However, our experimental results show that standard routing mechanisms like most reliable or cheapest energy paths are usually good. Our game-theoretically oriented algorithm - Fair Team RQR compares favorably to the other standard routing algorithms.

We have also developed a game theoretic paradigm for length- energy-constrained in a clustered sensornet architecture in which cluster heads utilize the underlying network infrastructure for communication. The three protocols i.e., LCGR, MEGR and TCGR find length-energy-constrained paths corresponding to the equilibrium of the routing game. They also balance energy consumption across the network by selecting new optimal paths periodically. The simulation results indicate effectiveness of these protocols for enhancing network survivability.